



Holden, P. B., Edwards, N. R., Ridgwell, A., Wilkinson, R. D., Fraedrich, K., Lunkeit, F., Pollitt, H. E., Mercure, J. F., Salas, P., Lam, A., Knobloch, F., Chewpreecha, U., & Viñuales, J. E. (2018). Climate-carbon cycle uncertainties and the Paris Agreement. *Nature Climate Change*, 8(7), 609-613. <https://doi.org/10.1038/s41558-018-0197-7>

Peer reviewed version

Link to published version (if available):  
[10.1038/s41558-018-0197-7](https://doi.org/10.1038/s41558-018-0197-7)

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PDF-document

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# Climate-carbon cycle uncertainties and the Paris Agreement

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40 **Abstract 203/200 words**

41 **Main text 1987/2000 words, 29/30 refs, 5/5 display items**

42 **Methods 2266/3000 words, 21 refs.**

43

44 **The Paris Agreement[1] aims to address the gap between existing climate policies and**  
45 **policies consistent with ‘holding the increase in global average temperature to well**  
46 **below 2C’. The feasibility of meeting the target has been questioned both in terms of the**  
47 **possible requirement for negative emissions[2], and ongoing debate on the sensitivity of**  
48 **the climate-carbon cycle system[3]. Using a sequence of ensembles of a fully dynamic**  
49 **three-dimensional climate-carbon cycle model, forced by emissions from an integrated**  
50 **assessment model of regional-level climate policy, economy, and technological**  
51 **transformation, we show that a reasonable interpretation of the Paris Agreement is still**  
52 **technically achievable. Specifically, limiting peak (decadal) warming to less than 1.7°C,**  
53 **or end-century warming to less than 1.54°C, occurs in 50% of our simulations in a**  
54 **policy scenario without net negative emissions or excessive stringency in any policy**  
55 **domain. We evaluate two mitigation scenarios, with 200 GTC and 307 GTC post-2017**  
56 **emissions, quantifying spatio-temporal variability of warming, precipitation, ocean**  
57 **acidification and marine productivity. Under rapid decarbonisation decadal variability**  
58 **dominates the mean response in critical regions, with significant implications for**  
59 **decision making, demanding impact methodologies that address non-linear spatio-**  
60 **temporal responses. Ignoring carbon-cycle feedback uncertainties (explaining 47% of**  
61 **peak warming uncertainty) becomes unreasonable under strong mitigation conditions.**

62

63 **A widely-held misconception is that given ~1°C warming to-date, and considering committed**  
64 **warming concealed by ocean thermal inertia, the 1.5°C target of the Paris Agreement[1] is**

65 already impossible. However, it is cumulative emissions that define peak warming[4]. When  
66 carbon emissions cease, terrestrial and marine sinks are projected to draw down atmospheric  
67 CO<sub>2</sub>, approximately cancelling the lagging warming. While the sign of this “zero emissions  
68 commitment” is uncertain, its contribution can be neglected for low CO<sub>2</sub> scenarios[5].  
69 Therefore, at least when considering CO<sub>2</sub> emissions in isolation, the 1.5°C target will remain  
70 physically achievable until the point that it has been crossed. The physical achievability of  
71 the Paris target has been demonstrated in a complex carbon cycle model with a simplified  
72 atmosphere[6] and updated recently using a simple carbon cycle model forced by a modified  
73 RCP2.6 scenario[7] and by policy-driven scenarios with substantial reliance on negative  
74 emissions technology[8]. Here, we demonstrate that the target is achievable using a fully-  
75 dynamic three-dimensional climate-carbon cycle model forced with emissions from a  
76 detailed set of sectorally and regionally specific mitigation policies without net negative  
77 emissions (methods).  
78  
79 We use the intermediate-complexity three-dimensional Earth system model PLASIM-  
80 GENIE[9], a model with similar ocean, atmosphere and carbon cycle dynamics to full  
81 complexity models, but with simpler parameterisations and lower spatial resolution. The  
82 model will not produce the full range of small-scale variability in high-complexity models,  
83 but it has the computational efficiency to allow a comprehensive treatment of uncertainties  
84 cognizant, for instance, of ongoing discussions on the state dependency of climate  
85 sensitivity[10,11] and ocean heat uptake efficacy[12]. We evaluate climate-carbon cycle  
86 uncertainty using a 69-member history-matched[13] ensemble designed from 940 training  
87 simulations (see methods). The ensemble climate sensitivity is 2.6 to 4.5°C (90%  
88 confidence), which compares to 1.9 to 4.5°C in CMIP5[14]. The transient climate response is

89 1.1 to 1.8°C, 1.2 to 2.4°C in CMIP5[14]. Ensemble ocean heat uptake (1965 to 2004) is 207  
 90 to 330 ZJ, 182 to 363 ZJ (1970 to 2010) in IPCC[14].  
 91  
 92 We validate the history-matched ensemble in Table 1A, by comparison with the CMIP5  
 93 multi-model ensembles forced by Representative Concentration Pathway (RCP) 2.6  
 94 (mitigation scenario) and RCP8.5 ('business-as-usual' scenario)[15]. Under RCP8.5, the  
 95 PLASIM-GENIE end-century CO<sub>2</sub> concentration, global warming and Atlantic Meridional  
 96 Overturning Circulation (AMOC) strength[14,16] are remarkably consistent with the CMIP5  
 97 ensemble, illustrating that uncertainties in transient climate sensitivity, carbon cycle  
 98 sensitivity and AMOC stability capture the spread of high complexity models. Mean surface  
 99 pH is also well represented, the significantly lower uncertainty in CMIP5 pH[17] arises  
 100 because these particular CMIP5 simulations were concentration forced. Overstated impacts in  
 101 marine productivity are apparent relative to CMIP5[17], but there is significant overlap in the  
 102 highly uncertain distributions. Under RCP2.6 forcing, there is a less complete analysis of  
 103 CMIP5 outputs. The PLASIM-GENIE ensemble understates the mean warming in RCP2.6 by  
 104 0.3°C relative to CMIP5, under-estimating the warmest ensemble members (Table 1A). We  
 105 therefore apply 0.3°C to bias-correct warming estimates in the rapid decarbonisation  
 106 scenarios (Table 1B).  
 107  
 108 Our future simulations are forced with emissions from policy scenarios of the simulation-  
 109 based integrated assessment model E3ME-FTT-GENIE[18]. The E3ME macroeconomic  
 110 model differs fundamentally from the equilibrium models more usually used to assess climate  
 111 policy by representing realistic (non-optimal) behaviour based on empirical relationships, and  
 112 by relaxing the constraint of a fixed money supply. Investment in renewables therefore can in  
 113 principle generate economic stimulus, for instance through increased employment[19].

Furthermore, the framework is suited to flexible application of a range of policy implementations that are not limited to a carbon tax, including regulations, subsidies, focussed taxation policies and public procurement. The model contains a bottom-up representation of technological diffusion in multiple-sectors (FTT) and is connected to a climate-carbon cycle model (GENIE) with a single-layer atmosphere. We consider three scenarios: 1) Current policy *CP*[18,20], 2) *2P0C*[18,20], rapid decarbonisation policies to avoid 2°C peak warming with 75% confidence (according to GENIE) and 3) *IP5C* (methods), representing our most optimistic set of policy assumptions, avoiding 1.5°C peak warming with 50% confidence.

Time series for the PLASIM-GENIE ensembles forced with the three policy scenarios are illustrated in Fig 1, and ensemble distributions are summarised in Table 1B. Note that the time series of ensemble median values do not correspond to fixed simulations, thus the distribution of peak decadal warming (Table 1B) show slightly higher values as individual trajectories cross owing to decadal variability. Steady-state decadal variability of mean surface temperature in PLASIM-GENIE is  $\pm 0.08^{\circ}\text{C}$  (one standard deviation).

Small differences in assumptions can make significant differences to cumulative emissions budgets under strong mitigation, noting that  $0.1^{\circ}\text{C}$  incremental warming is equivalent to  $\sim 50\text{GTC}$ [4]. Here, we consider both maximum and end-century change, as the former is most relevant for impact assessment and most consistent with the text of the Paris Agreement, with change expressed relative to a preindustrial (1856-1885) baseline taken from ensembles of 1805-2105 AD transient simulations. RCP2.6 non- $\text{CO}_2$  forcing is applied for both mitigation scenarios, and RCP8.5 non- $\text{CO}_2$  forcing for the current-policy scenario.

Bias-corrected median peak warming estimates (Table 1B) are 1.82°C (2P0C) and 1.70°C (1P5C), and 2100 estimates are 1.71°C and 1.54°C. Correlations suggest an increasing relative contribution of carbon-cycle processes to warming under rapid decarbonisation (Table S1). The response of the maximum value of Atlantic meridional overturning circulation (AMOC) in the mitigation scenarios is notable. The simulated expected peak weakening to 84% of preindustrial (Table 1B) arises from natural variability (steady-state decadal variability is 0.9Sv); the median response through the Century is steady (Fig1). However, in one 1P5C and two 2P0C simulations the AMOC reduces to ~50% of its present-day strength. We therefore cannot rule out significant AMOC weakening under mitigation, but note the suggestion of a reduction in the probability of this unlikely event under accelerated decarbonisation.

We now consider the mean climate-change patterns for a range of impact-relevant climate stressors: decadal DJF surface air temperature (Fig 2A), decadal JJA precipitation (Fig 3A), annual surface ocean acidity (Fig 4A) and annual marine primary productivity (Fig 4D). Patterns are 1P5C ensemble averages of (2090 minus 1990) change, expressed per 1°C mean ensemble warming. The mean patterns of changes of temperature and precipitation are broadly consistent with CMIP5 projections. Changes in pH (Fig 4A) result from increased concentrations of dissolved CO<sub>2</sub> and the associated reduction in carbonate ion concentrations approximately uniform across the surface ocean, except in the Arctic where amplified CO<sub>2</sub> uptake is apparent under melting sea ice[21]. This pattern is robust, explaining more than 95% of the variability in the ensemble (quantified through singular vector decomposition); a similar robust pattern of acidification was found in CMIP5[17]. Changes in primary productivity (Fig 4D) are dominated by large reductions of up to ~10% per °C of warming that are simulated in the Equatorial Pacific. Significant reductions are also simulated in mid-

latitude Pacific and Indian oceans, and in the Equatorial and high-latitude Atlantic. Despite the simplified ecosystem model[22], the patterns and magnitudes of productivity change are consistent with CMIP5 analysis; in RCP8.5, decreases of up to 30-50% are simulated in these regions[17], attributed to increased ocean stratification and slowed circulation, with consequent reductions in nutrient supply[23]. Increases in productivity are apparent in the Arctic and in parts of the Southern and Indian Oceans, here likely attributable to increased nutrient supply[24]. In stark contrast to pH, the pattern of productivity change explains only 20% of ensemble variability.

The ensemble-projections are now used to quantify spatio-temporal uncertainty by evaluating the adequacy of the approximations made in “pattern scaling”[25], a widely used approach to estimating climate fields for impacts evaluation. In pattern scaling an average climate response is calculated, typically as a multi-decadal average pattern of change. The pattern, normalised per °C global mean warming, is then scaled as appropriate for scenarios of interest. The strengths and limitations of pattern scaling, including modified approaches, have recently been reviewed[26]. It is known to be less accurate under strong mitigation[27].

Figures 2B, 3B, 4B and 4E plot the normalised mean field difference (1P5C – CP), capturing non-linear scenario-dependent feedbacks, and examining the pattern-scaling approximation of a scenario-invariant pattern. The temperature pattern differences reveal modest changes, for instance in the northern Atlantic, where the stronger AMOC leads to relatively warmer temperatures under mitigation. The largest precipitation pattern differences are associated with the Indian and SE Asian monsoons. The magnitudes of pH change patterns are very different in the two scenarios, approximately -0.1pH unit per °C under current policy and -0.03 per °C for rapid decarbonisation. This difference reflects the different response times of



pH and temperature to changing CO<sub>2</sub>. The 2090 temperature is influenced by cumulative excess CO<sub>2</sub> but the surface pH in 2090 is determined by 2090 CO<sub>2</sub> with no significant lag; mitigation acts at the timescale of natural CO<sub>2</sub> sinks to reduce acidification impacts on the surface ocean. In contrast, the patterns of change of marine productivity in the two scenarios are spatially different, with amplified relative reductions in the Atlantic, Indian and Southern Oceans, and a reduced relative reduction in the Equatorial Pacific.

The most important error when using pattern scaling arises from the neglect of variability. This emerges from two distinct sources, the neglect of model uncertainty and the neglect of natural variability, both of which alter the pattern of change itself. It is well established that natural variability, which has a magnitude that differs with location, is a critical limiting factor for the accuracy of climate projections and impact evaluation[28]. If we assume that the spread of climate model outputs encompasses possible reality, then model error can be estimated by applying the patterns from different climate models to test robustness of the impacts that result. However, internal variability is generally not considered, and pattern scaling impacts are derived from climate means. Under strong mitigation we argue this neglect may be inappropriate. The signal-noise ratio in strong mitigation scenarios is of order one and, for instance, decadal variability will be a significant contributor to the uncertainty in determining peak (~2050 AD) climate change.

In the final columns of Figs 2, 3 and 4, each 1P5C simulation anomaly field is normalised by its respective warming, and the RMS ensemble variability about the 1P5C scenario mean is plotted. For the climate fields (Figs 2 and 3), comparison of variability about the mean fields 30-year averages (predominantly parametric uncertainty) and 10-year averages (internal and parametric uncertainty) relative to a 30-year baseline, indicates that the two sources of

variability are comparable in amplitude. For the ocean impact fields (Fig 4) the variability is derived from annual averages. In all fields, the uncertainties in the patterns (1P5C - CP) are dominated by the variability about the pattern (right panels). The uncertainties often dominate even the mean response. For instance, in parts of the Arctic, RMS uncertainty of  $\sim 3^{\circ}\text{C}$  per  $^{\circ}\text{C}$  warming compares to a mean signal of  $\sim 3^{\circ}\text{C}$  (Fig 2, Table S2), while RMS uncertainty of precipitation is comparable to the mean signal in monsoon regions (Fig3, Table S2). Simulations forced by current-policy emissions are associated with significantly lower fractional uncertainty (Table S2), reflecting an increased signal-noise ratio, and demonstrating that the assumptions of pattern scaling are well justified under high-emission scenarios.

The implications of our findings for policy-making are important: if policy and market-based responses to climate change are sufficient to uphold the level of ambition of the Paris Agreement, climate change impacts could still be of large amplitude in sensitive regions such as the Arctic. However, in these scenarios, uncertainties from model error and internal variability can dominate expected mean patterns. Consequently, we argue that a paradigm shift in impacts evaluation is now essential to support decision making. Estimates based on mean patterns of change will be insufficient. Instead, statistical methodologies developed to address non-linear spatio-temporal feedbacks[29] will need to be extended to high-complexity models. Holding the increase in (multi-decadal) global average temperature above pre-industrial to  $1.5^{\circ}\text{C}$  appears still to be possible, but results in a world where the superposition of climate change onto natural variability is key to understanding impacts on *inter alia* ecosystems, biodiversity, ice sheets and permafrost stability.

**Author contributions**

239

240 PBH, NRE and RDW designed and coordinated the Earth system modelling. HP, JFM and  
241 NRE designed and coordinated the energy-economy modelling. PBH, NRE, RDW and HP  
242 wrote the article with contributions from all. PBH performed the PLASIM-GENIE  
243 simulations. UC performed the E3ME-FTT simulations. All authors developed model  
244 components and/or provided scientific support: PBH (ESM coupling), KF and FL  
245 (atmosphere), NRE (ocean), AR (biogeochemistry), HP and JFM (energy-economic), PS and  
246 JFM (power sector), AL and JFM (transport sector), FK and JFM (household heating), JV  
247 (geopolitics), RDW (statistics).

248

#### 249 **Acknowledgements**

250 The authors acknowledge C-EERNG and Cambridge Econometrics for support, and funding  
251 from EPSRC (JFM, fellowship no. EP/ K007254/1); the Newton Fund (JFM, PS, JV, EPSRC  
252 grant no EP/N002504/1 and ESRC grant no ES/N013174/1), NERC (NRE, PH, HP, grant no  
253 NE/P015093/1), CONICYT (PS), the Philomathia Foundation (JV) and Horizon 2020 (HP,  
254 JFM; Sim4Nexus project).

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258 declare no competing financial interests. Readers are welcome to comment on the online  
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#### 262 **References**

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264 [1] *Adoption of the Paris Agreement* FCCC/CP/2015/L.9/Rev. 1 (UNFCCC, 2015);  
 265 <http://unfccc.int/resource/docs/2015/cop21/eng/l09r01.pdf>

266 [2] Anderson, K. and Peters, G. The trouble with negative emissions *Science* **6309** 182-183  
 267 (2016)

268 [3] Friedlingstein, P., et al. Uncertainties in CMIP5 climate projections due to carbon cycle  
 269 feedbacks *Journal of Climate* **27** 511-526 (2103)

270 [4] Allen, M.R. et al. Warming caused by cumulative carbon emissions towards the trillionth  
 271 tonne *Nature* **458** 1163-1166 (2009)

272 [5] Ehlert, D. and Zickfeld, K. What determines the warming commitment after cessation of  
 273 CO<sub>2</sub> emissions? *Env. Res. Lett.* **12** 0015002 (2017)

274 [6] Steinacher, M., Joos, F., and Stocker, T. F.: Allowable carbon emissions lowered by  
 275 multiple climate targets, *Nature*, **499**, 197-201 (2013)

276 [7] Millar, R.J. et al. Emission budgets and pathways consistent with limiting warming to  
 277 1.5°C, *Nature Geoscience*, doi 10.1038/NGE03031 (2017)

278 [8] Rogelj, J. et al Scenarios towards limiting global mean temperature increase below 1.5°C  
 279 *Nature Climate Change* doi:10.1038/s41558-018-0091-3 (2018)

280 [9] Holden, P.B. et al. PLASIM–GENIE v1.0: a new intermediate complexity AOGCM  
 281 *Geosci. Mod. Dev.* **9** 3347-3361 (2016)

282 [10] Geoffroy, O., Saint-Martin, D., Olivié, D. J. L., Voldoire, A., Bellon, G., and Tytéca, S.:  
 283 Transient Climate Response in a Two-Layer Energy-Balance Model. Part I: Analytical  
 284 Solution and Parameter Calibration Using CMIP5 AOGCM Experiments, *Journal of Climate*,  
 285 26, 1841-1857, 10.1175/jcli-d-12-00195.1, 2012.

286 [11] Gregory, J. M., Andrews, T., and Good, P.: The inconstancy of the transient climate  
 287 response parameter under increasing CO<sub>2</sub>, *Philosophical Transactions of the Royal Society*  
 288 A: Mathematical, Physical and Engineering Sciences, 373, 2015.

289 [12] Winton, M., Takahashi, K., and Held, I. M.: Importance of Ocean Heat Uptake Efficacy  
 290 to Transient Climate Change, *Journal of Climate*, 23, 2333-2344, 10.1175/2009jcli3139.1,  
 291 2010.

292 [13] Williamson, D. et al. History matching for exploring and reducing climate model  
 293 parameter space using observations and a large perturbed physics ensemble. *Climate*  
 294 *dynamics* **41**, 1703–1729 (2013)

295 [14] *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to*  
 296 *the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* Cambridge  
 297 University Press, Cambridge, United Kingdom and New York, NY, USA (2013)

298 [15] Meinshausen, M. et al. The RCP greenhouse gas concentrations and their extensions  
 299 from 1765 to 2300. *Climatic Change* **109**, 213-241 (2011)

300 [16] Cheng, W., Chiang, J.C.H. & Zhang, D. Atlantic Meridional Overturning Circulation  
 301 (AMOC) in CMIP5 Models: RCP and Historical Simulations. *J. Clim.* **26**, 7187-7197 (2013)

302 [17] Bopp, L. et al. Multiple stressors of ocean ecosystems in the 21<sup>st</sup> century: projections  
 303 with CMIP5 models. *Biogeosci.* **10**, 6225-6245 (2013)

304 [18] Mercure, J.-F. et al. Environmental impact assessment for climate change policy with the  
 305 simulation-based integrated assessment model E3ME-FTT-GENIE *Energy Strategy Reviews*  
 306 **20** 195-208 (2018a)

307 [19] Pollitt, H. & Mercure J.-F. The role of money and the financial sector in energy-  
 308 economy models used for assessing climate and energy policy. *Climate Policy*  
 309 <http://dx.doi.org/10.1080/14693062.2016.1277685> (2017)

310 [20] Mercure, J.-F. et al, Macroeconomic impact of stranded fossil-fuel assets, in press  
 311 *Nature Climate Change* (2018b)

- [21] Yamamoto, A., Kawamiya, M., Ishida, A., Yamanaka, Y., and Watanabe, S. Impact of rapid sea-ice reduction in the Arctic Ocean on the rate of ocean acidification, *Biogeosciences* **9**, 2365–2375 (2012).
- [22] Ridgwell, A. et al. Marine geochemical data assimilation in an efficient Earth System Model of global biogeochemical cycling *Biogeosciences* **4**, 87–104 (2007)
- [23] Steinacher, M. et al. Projected 21st century decrease in marine productivity: a multi-model analysis. *Biogeosciences* **7**, 979–1005 (2010).
- [24] Rykaczewski, R. R. and Dunne, J. P.: Enhanced nutrient supply to the California Current Ecosystem with global warming and increased stratification in an earth system model, *Geophys. Res. Lett.*, **37**, L21606, doi:10.1029/2010GL045019, 2010.
- [25] Santner B.D., Wigley T.M.L., Schlesinger M.E., Mitchell J.F.B. *Developing climate scenarios from equilibrium GCM results*, Hamburg, Germany (1990)
- [26] Tebaldi, C. & Arblaster, J.M. Pattern scaling: Its strengths and limitations, and an update on the latest model simulations. *Climatic Change* **122**, 459-471 (2014)
- [27] Wu, P., Wood, R., Ridley, J. & Lowe, J. Temporary acceleration of the hydrological cycle in response to a CO<sub>2</sub> rampdown. *Geophys Res Lett* **37**, L12705 (2010)
- [28] Deser, C., Knutti, R., Solomon, S. and Phillips, A.S.: Communication of the role of natural variability in future North American climate, *Nature Climate Change*, **2**, 775 (2012)
- [29] Holden, P.B, Edwards, N.R., Garthwaite, P.H. and Wilkinson, R.D. Emulation and interpretation of high-dimensional climate outputs, *J. App. Stats.* **42**, 2038-2055 (2015)

<b>A</b>	<b>RCP2.6</b>		<b>RCP8.5</b>	
	CMIP5	PLASIM-GENIE	CMIP5	PLASIM-GENIE
Warming (°C)	1.0 ± 0.4 (0.3, 1.7)	0.7 ± 0.2 (0.4, 1.0)	3.7 ± 0.7 (2.6, 4.8)	3.6 ± 0.6 (2.6, 4.4)
CO <sub>2</sub> (ppm)		402 ± 19 (373, 429)	985 ± 97 (794, 1142)	1010 ± 110 (829, 1185)
AMOC (% change)		-6 ± 10 (-17, 4)	(-60, -15)	-32 ± 12 (-54, -16)
Surface pH (pH)	-0.07 ± 0.001	-0.04 ± 0.01 (-0.069, -0.028)	-0.33 ± 0.003	-0.33 ± 0.04 (-0.41, -0.27)
Productivity (%)	-2.0 ± 4.1	-2.7 ± 1.2 (-4.8, -1.2)	-8.6 ± 7.9	-15.1 ± 4.1 (-21.7, -7.43)

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<b>B</b>	<b>Current policies</b>	<b>2P0C policies</b>	<b>1P5C policies</b>
Peak decadal warming (°C)	(2.54, 3.12, <b>4.18</b> , 5.17, 5.47)	(1.09, 1.19, <b>1.52</b> , 1.95, 2.02)	(1.04, 1.11, <b>1.40</b> , 1.74, 1.85)
Peak annual CO <sub>2</sub> (ppm)	(649, 703, <b>863</b> , 996, 1048)	(394, 405, <b>446</b> , 485, 493)	(381, 391, <b>429</b> , 458, 468)
Min decadal AMOC (%)	(33, 44, <b>68</b> , 80, 87)	(43, 76, <b>83</b> , 90, 95)	(51, 74, <b>84</b> , 90, 94)
Max annual surf acidification (pH)	(-0.50, -0.47, <b>-0.39</b> , -0.31, -0.27)	(-0.22, -0.19, <b>-0.15</b> , -0.12, -0.10)	(-0.19, -0.17, <b>-0.14</b> , -0.10, -0.09)
2100 decadal warming (°C)	(2.54, 3.12, <b>4.18</b> , 5.17, 5.47)	(0.73, 1.10, <b>1.41</b> , 1.81, 1.87)	(0.63, 0.97, <b>1.24</b> , 1.61, 1.67)
2105 annual CO <sub>2</sub> (ppm)	(649, 703, <b>863</b> , 996, 1048)	(371, 382, <b>415</b> , 445, 453)	(357, 367, <b>394</b> , 416, 427)
2100 decadal AMOC (%)	(33, 45, <b>69</b> , 83, 91)	(43, 79, <b>90</b> , 102, 104)	(52, 82, <b>92</b> , 101, 107)
2105 annual surf acidification (pH)	(-0.50, -0.47, <b>-0.39</b> , -0.31, -0.27)	(-0.19, -0.17, <b>-0.13</b> , -0.10, -0.09)	(-0.16, -0.15, <b>-0.11</b> , -0.09, -0.08)
2105 annual productivity (%)	(-33.7, -24.3, <b>-13.8</b> , -4.6, -3.5)	(-9.5, -5.0, <b>-3.0</b> , -1.1, -0.8)	(-5.7, -4.1, <b>-2.2</b> , -0.7, -0.1)
<b>Bias corrected peak warming (°C)</b>		(1.39, 1.49, <b>1.82</b> , 2.25, 2.32)	(1.34, 1.41, <b>1.70</b> , 2.04, 2.15)
<b>Bias corrected 2100 warming (°C)</b>		((1.03, 1.40, <b>1.71</b> , 2.11, 2.17)	(0.93, 1.27, <b>1.54</b> , 1.91, 1.97)

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338 **Table 1: A) PLASIM-GENIE validation against multi-model ensembles of**  
339 **Representative Concentration Pathways.** Data are expressed as 2090-1990 decadal  
340 anomalies except for CO<sub>2</sub> which is 2100 concentration and PLASIM-GENIE productivity  
341 which is 2105-2005 anomaly. The 1990 PLASIM-GENIE baselines are 30-year averages  
342 (1976-2005) except for ocean pH and productivity (where annual averages are used for all  
343 analysis). Ensembles are summarised as mean ± 1 standard deviation (5<sup>th</sup> and 95<sup>th</sup>  
344 percentiles), except for CMIP5 CO<sub>2</sub> and AMOC where the bracketed ranges represent 11-  
345 member and 10-member ensemble spreads respectively. **B) PLASIM-GENIE summary**  
346 **confidence intervals of the E3ME-FTT-GENIE-1 scenarios.** Minima, 5<sup>th</sup> percentile,  
347 median, 95<sup>th</sup> percentile and maxima of the 69-member ensembles. Warming, AMOC and  
348 acidification are expressed relative to a 30-year average baseline centred on 1870.  
349 Productivity is 2105-2005 anomaly. The 0.3°C bias correction under strong mitigations is  
350 implied by the RCP2.6 CMIP5 comparison (Table 1A).

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## Figure Captions

**Figure 1: Summary time series of the 69-member Current-Policy, 2P0C and 1P5C E3ME-FTT-GENIE emissions-forced PLASIM-GENIE ensembles.**

**Figure 2: December-January-February surface air temperature scaling patterns and uncertainty.** Scaling patterns are 1P5C and CP ensemble means (2086-2095 minus 1976-2005, °C) normalised per 1°C warming. Ensemble variability is calculated by normalising each ensemble member per 1°C warming and calculating the RMS difference with respect to the mean pattern (A). Variability is derived for both (C) 10-year (2086-2095) and (D) 30-year (2076-2105) patterns to help isolate the contributions of decadal variability and parametric uncertainty.

**Figure 3: June-July-August precipitation scaling patterns and uncertainty.** Scaling patterns are 1P5C and CP ensemble means (2086-2095 minus 1976-2005, mm/day) normalised per 1°C warming. Ensemble variability is calculated by normalising each ensemble member per 1°C warming and calculating the RMS difference with respect to the mean pattern (A). Variability is derived for both (C) 10-year (2086-2095) and (D) 30-year (2076-2105) patterns to help isolate the contributions of decadal variability and parametric uncertainty.

**Figure 4: Ocean stressor scaling patterns and uncertainty.** Top: surface pH, pH units per °C warming. Bottom: marine productivity, fractional change per °C warming. Scaling patterns (left) are 1P5C ensemble means (2105-2005), and 1P5C - CP scaling pattern difference (centre). Ensemble variability is calculated by normalising each ensemble member per 1°C warming and calculating the RMS difference with respect to the appropriate mean pattern. All data are annually averaged.



## Methods

**PLASIM-GENIE** is a coupling of the intermediate-complexity spectral atmosphere model PLASIM[30] to the Grid-Enabled Integrated Earth system model GENIE[31]. The coupling and climatology are described in detail in [9]. PLASIM-GENIE is not flux corrected; the moisture flux correction required in the original tuning[9] was removed during the history-matching calibration (see below). We here apply PLASIM-GENIE with carbon-coupled biosphere modules BIOGEM and ENTS, described in [31] for the energy-moisture balance atmosphere configuration. We apply BIOGEM with the default Michaelis-Menton phosphate-limited productivity scheme[22]. The carbon-cycle model has been extensively validated through model inter-comparisons[32,33].

Important neglects of the PLASIM-GENIE carbon cycle are anthropogenic land-use change, peat and permafrost. These omissions tend to overstate the terrestrial carbon sink (by overstating natural forest) and they neglect potentially significant terrestrial sources (from peat and permafrost). We note that the history-matching calibration is designed to subsume such structural deficiencies (here, for instance, into CO<sub>2</sub> fertilization and soil respiration).

PLASIM-GENIE is freely available. Please contact the authors for information.

**Atmosphere-ocean gearing.** PLASIM-GENIE simulates approximately 2.5 years per CPU hour, so that 2,000-year spin-ups take one month of computing. In order to enable the exploration of parameter space, the implementation of an atmosphere-ocean gearing approach was required. The spin-up simulation time is determined by the ocean timescale, but the simulation speed of the model is determined by the atmosphere, which uses approximately 99% of the CPU demands of the physical model. In gearing mode, applied only to

equilibrium spin-ups, the model alternates between a conventionally coupled mode (for 1 year) and a fixed-atmosphere mode (for 9 years), reducing spin-up CPU time by an order of magnitude. During the conventional coupling mode, atmosphere-ocean coupling variables are accumulated and saved as daily averages. These variables comprise energy fluxes, moisture fluxes and wind stresses. During the fixed atmosphere phase, the atmospheric variables are kept constant and these daily averaged fluxes are applied to the ocean. Latent heat, sensible heat and longwave radiation ocean heat loss are recalculated at every atmosphere time step during the fixed atmosphere phase, when energy conservation is therefore not imposed. This is necessary for numerical convergence because these fluxes depend upon ocean temperature, which evolves during the fixed atmosphere phase. Evaporation is not recalculated during the fixed atmosphere phase in order to ensure moisture conservation. AO-g geared spin-up states are consistent with the standard model, as demonstrated by smooth spun-on historical transient simulations in all ensemble members, though we note that rapid (sub-decadal) and modest (a few Sv) AMOC adjustments are seen in some simulations, arising from different inter-annual variability.

**Experimental design.** Each model configuration was spun-up with a 2,000-year AO-g geared quasi-equilibrium preindustrial simulation, with atmospheric CO<sub>2</sub> relaxed to 278ppm. Simulations were continued as emissions-forced historical transient simulations (AO-gearing off, CO<sub>2</sub> freely evolving). Historical forcing (1805 to 2005) comprised anthropogenic CO<sub>2</sub> emissions and non-CO<sub>2</sub> radiative forcing. Fossil fuel, cement and gas flaring emissions were prescribed from CMIP5 (<https://cmip.llnl.gov/cmip5/forcing.html>) and were combined with ISAM C-N land-use change emissions[34] from the HYDE land-use dataset[35]. Non-CO<sub>2</sub> forcing data was taken from [15] implemented in PLASIM-GENIE as effective CO<sub>2</sub>. Future (2005-2105) emissions were taken from the E3ME-FTT-GENIE scenarios, scaled by

9.82/8.62, to match estimated 2015 total emissions[36], accounting for sources not represented in E3ME. Future land use change emissions and non-CO<sub>2</sub> radiative forcing were taken from RCP2.6 (1P5C and 2P0C scenarios) and RCP8.5 (CP scenario).

### **History-matched ensemble**

Carefully designed ensembles of simulations are central to our approach to quantifying Earth system uncertainties. We applied a ‘history matching’ calibration strategy[13,37], sampling throughout high-dimensional model input space to identify model configurations that are capable of producing reasonable simulations in the PLASIM-GENIE Earth system model, and then running the plausible configurations forward to characterise uncertainty about the future. Each configuration is required only to provide a ‘plausible’ simulation[38], thereby avoiding the introduction of bias through over-fitting[39]. A configuration is ruled out only if it is inconsistent with an observation, allowing for the imperfections of both model and data. Thus, the history matching philosophy generates simulations that encompass the full range of realistic dynamical feedbacks implemented in model[40].

In PLASIM-GENIE, identifying large numbers of history-matched configurations would be prohibitively demanding computationally. We render the problem tractable by using emulators[41] to search throughout model input space. The emulators are trained on a sequence of preliminary ensembles amounting to 1.9 million years of climate simulation in total (940 completed simulations). The process produced 69 model variants, each validated by simulation, having considered hundreds of millions of randomly sampled parameter configurations in the emulator. The final models all adequately simulate ten key global-scale observational targets including surface air temperature, vegetation and soil carbon, Atlantic,

Pacific and Southern Ocean circulation measures, dissolved O<sub>2</sub> and calcium carbonate flux,  
and transient temperature and CO<sub>2</sub> changes (Table S4).

For the purposes of the history matching, the simulator (here applied to the preindustrial spin-up state) can be considered as a function that maps from 32 input parameters (Table S3) to the eight different outputs (Table S4). Our aim is to infer the input values that lead to outputs within the plausible climate ranges as defined in Table S4. It is not possible to naively explore the simulator output over the full input parameter ranges by repeatedly evaluating the simulator, as for example, just doing one evaluation in each corner of the input space would require  $2^{32} \approx 10^9$  model evaluations. Instead, we build emulators[41,42] that mimic the simulator response surface, and allow us to predict its value for any input. An initial large exploratory analysis was performed, motivated by the iterated waves approach[39]. Starting from a 100-member maximin latin hypercube ensemble, sequential series of 100-member ensembles were performed, probing regions of likely plausible space by using stepwise-selected linear regression models that were continually refitted as simulations completed. This produced 940 completed simulations that we used to train the final history match. Part of the motivation for the exploratory ensemble was to develop a general understanding of the range of model responses. Most notably it enabled us to identify regions of parameter space that satisfied the plausibility constraints without flux correction so that the associated parameter (APM, Table S3) could be fixed at zero for the final history match.

For the final history match, a variety of emulation approaches were considered, including stepwise regression, the LASSO[43] which is a regularized version of linear regression, and Gaussian process regression with a combination of different mean and covariance functions[44]. To determine the optimal approach for each of the eight outputs, we split the

data into test and training datasets and evaluated the emulators' predictive performance (RMSE, statistical coverage), repeating the process 10 times to get an average performance. The optimised emulators were used to find input values that are expected to give plausible simulations (i.e. within tabulated ranges for all emulator-filtered metrics, Table S4), to generate a sample of design points which encapsulate the uncertainty about future climate. We used an approximate Bayesian computation type approach[45], using rejection sampling to sample parameters from the prior distribution and evaluating the probability of these values leading to plausible outputs, to generate a large number of plausible future climates, considering hundreds of millions of emulator evaluations. A final 200-member candidate ensemble for the future transient simulations was then chosen using a 'greedy' design, adding points to maximize a criterion that combined the probability the simulation would be plausible (according to the emulator), and the distance of candidate points to the other points already in the design, so as to ensure design points fully span the 32-dimensional plausible input space.

The 200 history-matched parameter sets were applied to PLASIM-GENIE, and 183 were accepted as giving plausible preindustrial climates in the simulator. These were spun on through the industrial period (1805 to 2005) with emissions and non-CO<sub>2</sub> radiative forcing. Sixty-nine simulations were selected as also having plausible climate sensitivity (2005 -1870 warming between 0.6 and 1.0K) and carbon cycle (2005 CO<sub>2</sub> in the range 355 to 403ppm). These 69 model configurations were applied in the future transient ensembles.

In total, 1140 spin-up simulations (2000 years each) were performed with the geared model and 345 transient simulations (300 years each) with the standard model, representing

approximately 15 CPU years of computing, corresponding to the CPU time needed to simulate a few decades with a CMIP5 type Earth System Model.

#### **Decarbonisation policies to meet 1.5°C and 2°C**

The E3ME-FTT-GENIE modelling framework and the particular policy scenarios used here have been described in detail elsewhere[18,20], below we give a summary of the policy choices taken as inputs to the modelling framework in deriving the emissions scenarios used here as input to PLASIM-GENIE. Three scenarios are used: a current-policy baseline, a scenario in which there is an 75% chance of limiting peak warming to 2°C and a scenario in which there is a 50% chance of limiting peak warming to 1.5°C.

The model baseline is consistent with the IEA's 'Current Policies' scenario[46]. The baseline can broadly be considered as a continuation of current trends; existing policy remains in place and has some lagged effects that continue into the projection period, but there is no additional policy stimulus. Most policy instruments in the baseline are implicitly accounted for through the data itself (e.g. diffusion trends).

The 1.5°C and 2°C scenarios are designed as sets of policies that are added to the baseline case. In almost all countries, these policies encapsulate the measures put forward in the INDCs that were submitted to the Paris COP and complement them with other measures in order to scale up the level of ambition of decarbonisation. The scenarios are designed from a 'bottom-up' perspective. Essentially, policies are added across the full range of economic sectors sequentially until the targets are met. The 1.5°C scenario includes all the measures in the 2°C scenario, plus additional ones, as described below.

557 Many of the policies are specific to particular sectors, but two economy-wide policies are  
558 implemented:

- 559 • The first measure is an economy-wide programme of energy efficiency. Our 2°C  
560 scenario assumes that the programmes are in line with the IEA's analysis[47] for a  
561 450ppm scenario (excluding houses, which are treated separately, see below). They  
562 are further scaled up 25% for the 1.5°C scenario.
- 563 • The second measure is a carbon tax that is applied equally across the world. The  
564 carbon tax rates rise to \$310.2/tCO<sub>2</sub> and \$96.4/tCO<sub>2</sub> by 2030 in the 1.5°C and 2°C  
565 scenarios respectively, and \$886.3/tCO<sub>2</sub> and \$274.8/tCO<sub>2</sub> by 2050. The carbon taxes  
566 are applied to all industrial sectors, but not to road transport nor households, where  
567 separate rates are levied (since these sectors are likely to, or already have, their own  
568 specific carbon or energy tax rates).

569

570 Building on [48], the following power sector policies were added to both scenarios:

- 571 • Feed-in-Tariffs - 100% of the difference between the levelised cost for wind and solar  
572 and a fixed value of \$80/MWh is paid by the grid to promote renewable uptake.
- 573 • Direct renewables subsidies – in most cases 50-60%, to provide an incentive to  
574 increase uptake, across a range of technologies (this is in addition to feed-in-tariffs).  
575 The subsidies gradually decrease over time and are phased out by 2050.
- 576 • In several countries there are immediate mandates to prevent the construction of new  
577 coal capacity.

578

579 In addition, it is assumed that electricity storage technologies advance up to 2050 such that  
580 the requirement for back-up flexible generation capacity (e.g. oil and gas peaking plants) is  
581 limited.

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583 Combinations of policies are used to incentivise the adoption of vehicles with lower  
584 emissions [49] in both scenarios. The list includes:

- 585 • fuel efficiency regulations of new liquid fuel vehicles
- 586 • a phase out of older models with lower efficiency
- 587 • kick-start programmes for electric vehicles where they are not available (by public  
588 authorities or private institutions, e.g. municipality vehicles and taxis)
- 589 • a tax of \$150/gCO<sub>2</sub>/km (2015 prices), to incentivise vehicle choice
- 590 • a fuel tax (increasing from \$0.10 in 2018 to \$1.00 per litre of fuel in 2050, 2015  
591 prices) to curb the total amount of driving
- 592 • increasing/introducing biofuel mandates between current values to between 10% and  
593 30% (40% in Brazil) in 2050, different for every country, extrapolating IEA  
594 projections [50] for the 2°C scenario, and to 97% in the 1.5°C scenario

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596 Aviation is assumed to switch to biofuels gradually over the period 2020-2050 (faster in the  
597 1.5°C scenario), but total bioenergy consumption remains within 150 EJ/yr.

598

599 The following policies were applied to homes in both scenarios:

- 600 • taxes on the residential use of fossil fuels, applied in Annex I and OPEC countries:  
601 starting at an equivalent of \$110/tCO<sub>2</sub> (2015 values) and linearly increasing to  
602 \$240/tCO<sub>2</sub> in 2030, constant at 2030 levels afterwards
- 603 • direct capital subsidies on renewable heating systems, applied globally: -40% on the  
604 purchase and installation of heat pumps, solar thermal systems and modern biomass  
605 boilers, phased out between 2030 and 2050



- kick-start programmes for renewable heating systems where they are not available, for a limited time period of five years (e.g. installations in publicly owned housing stock)

In some industrial sectors in East and South East Asia, a further mandate was added to electrify sectors that are currently dependent on coal (only in the 1.5°C scenario). Emissions from industrial processes are modelled as fixed in relation to real production levels from the relevant sector. In the baseline scenario, no efficiency improvements are assumed. In the 2°C and 1.5°C scenarios it is assumed that the production efficiency of process emissions improves by 3% a year over the projection period. Land-use change emissions are calculated in GENIE, with LUC assumed to follow RCP2.6 in the mitigation scenarios and RCP8.5 in the current policy baseline.

## **Data availability**

The data that support the findings of this study are available from the corresponding author upon request.

## **Methods References**

- [30] Fraedrich, K. A suite of user-friendly climate models: Hysteresis experiments *Eur. Phys. J. Plus* **127**, 53 (2012)
- [31] Lenton, T. M. et al. Millennial timescale carbon cycle and climate change in an efficient Earth system model *Climate Dynamics* **26**, 687–711 (2006)
- [32] Zickfeld, K. et al. Long-term climate change commitment and reversibility: An EMIC intercomparison *J. Climate* **26**, 5782– 5809 (2013)

631 [33] Joos, F. et al Carbon dioxide and climate impulse response functions for the computation  
632 of greenhouse gas metrics: a multi-model analysis *Atmos. Chem. Phys.* **13**, 2793-2825 (2013)

633 [34] Jain, A. K., Meiyappan, P., Song, Y., & House, J. I. CO<sub>2</sub> Emissions from land-use  
634 change affected more by nitrogen cycle, than by the choice of land cover Data *Global*  
635 *Change Biology* **19**, 2893-2906 (2013)

636 [35] Ramankutty, M. et al. Challenges to estimating carbon emissions from tropical  
637 deforestation *Global Change Biology* **13**, 51-66 (2007)

638 [36] Jackson, R.B. et al. Reaching peak emissions *Nature Climate Change* **6**, 7-10 (2016)

639 [37] Craig, P.S., Goldstein, M., Seheult A.H. & Smith, J.A. Pressure matching for  
640 hydrocarbon reservoirs: a case study in the use of Bayes linear strategies for large computer  
641 experiments in *Case Studies in Bayesian Statistics. Lecture Notes in Statistics* **121** Springer,  
642 New York, NY (1997)

643 [38] Edwards, N.R., Cameron, D. & Rougier, J. Precalibrating an intermediate complexity  
644 climate model. *Climate dynamics* **37**, 1469–1482 (2011)

645 [39] Williamson, D. B., Blaker, A.T. & Sinha, B. Tuning without over-tuning: parametric  
646 uncertainty quantification for the NEMO ocean model *Geoscientific Model Development* **10**,  
647 1789-1816 (2017)

648 [40] Holden, P.B., Edwards, N.R., Oliver, K.I.C., T. Lenton, T. M. & Wilkinson, R.D. A  
649 probabilistic calibration of climate sensitivity and terrestrial carbon change in GENIE-1.  
650 *Climate Dynamics* **35**, 785–806 (2010)

651 [41] Sacks, J., Welch, W.J., Mitchell, T.J. and Wynn, H.P. Design and analysis of computer  
652 experiments *Statistical Science* **4**, 409–23 (1989)

653 [42] O’Hagan, A. Bayesian Analysis of Computer Code Outputs: A Tutorial *Reliability*  
654 *Engineering & System Safety* **91**, 1290–1300 (2006)

- 655 [43] Tibshirani, R. Regression Shrinkage and Selection via the Lasso *Journal of the Royal*  
656 *Statistical Society. Series B (Methodological)*. **58**, 267–88 (1996)
- 657 [44] Rasmussen, C.E. *Gaussian processes in machine learning*, in *Advanced Lectures on*  
658 *Machine Learning*, O. Bousquet, U. von Luxburg, and G. Rätsch (Eds.) Springer, Berlin,  
659 Heidelberg, New York (2004)
- 660 [45] Marin, J.-M., Pudlo, P., Robert, C.P. & Ryder, R.J. Approximate Bayesian  
661 Computational Methods. *Statistics and Computing* **22**, 1167–1180 (2012)
- 662 [46] ‘World Energy Outlook’, 2015 edition, OECD/IEA, Paris.
- 663 [47] ‘World Energy Investment Outlook’, OECD/IEA, Paris.
- 664 [48] Mercure, J. F., Pollitt, H., Bassi, A. M., Viñuales, J. E. & Edwards, N. R. Modelling  
665 complex systems of heterogeneous agents to better design sustainability transitions policy.  
666 *Global Environmental Change* **37**, 102-115 (2016).
- 667 [49] Mercure, J.F., Lam, A., Billington, S. & Pollitt, H. Integrated assessment modelling as a  
668 positive science: modelling policy impacts in road transport to meet a climate target well  
669 below 2°C, pre-print at arXiv:1702.04133. (2018)
- 670 [50] ‘World Energy Outlook’, 2014 edition, OECD/IEA, Paris.







